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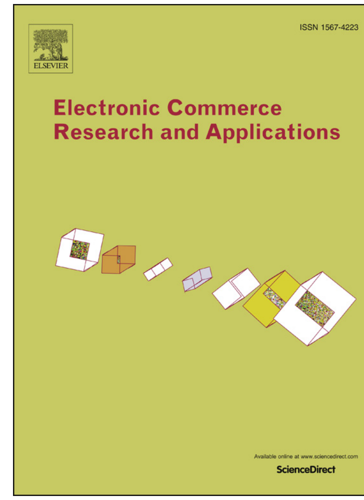


Service quality management of online car-hailing based on PCN in the sharing economy

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**Service quality management of online car-hailing based on PCN in the sharing economy**

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**Abstract:** Online car-hailing has successfully integrated the sharing economy into the transportation industry. However, with its rapid development, service issues remain a challenge, and continuously improving service quality is a key factor for the sustainable growth of online car-hailing and the sharing economy. In this study, we implement LSTM text classification, sentiment analysis and frequent itemset mining of the electronic word-of-mouth (eWOM) of the online car-hailing platform, Didi Chuxing (DiDi), to identify existing service issues. Then, we depict the service process network of online car-hailing by using process chain network (PCN) to analyze and locate service issues. Finally, we analyze service optimization and innovation for online car-hailing by proposing corresponding service quality optimization suggestions based on the optimization principles of PCN. By constructing a service quality management research framework of online car-hailing in the sharing economy, we contribute to the literature on service science and the sharing economy and provide practical implications for sharing economy platforms to establish data-driven strategies of operation management.

**Key words:** sharing economy; service quality; online car-hailing; PCN; eWOM

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**Service quality management of online car-hailing based on PCN in the sharing economy**

## 1. Introduction

The sharing economy promotes the efficient circulation of idle resources among different individuals, effectively improves the allocation efficiency of social resources, and is also a reflection of the concept of green consumption (Chase, 2015). The global market scale of the sharing economy attained approximately US$15 billion in 2015 and is expected to increase to US$335 billion by 2025 (PwC, 2015). As a new business model, the booming sharing economy is gradually changing people's consumption behavior and is further exerting a significant impact on original industrial ecology, employment, and social relations (Zuo and Chen, 2017).

Sharing economy research has been undertaken mainly in the context of developed economies, while less attention has been paid to emerging markets (e.g., China), the latter of which represent a fast-moving and prosperous market for sharing-economy businesses (Cheng, 2016). In China, the sharing economy platforms, exemplified by Didi Chuxing (DiDi), have successfully established the sharing economy in transportation and gradually changed people's consumption habits. In 2017, DiDi provided more than 7.43 billion online car-hailing services for 450 million users in more than 400 cities all over the world[1], and these services exceeded the four billion rides by Uber[2].

Despite its fast growth, online car-hailing has also exposed service issues. Service quality is the most critical factor for service failure, and the emphasis on improving service quality mainly lies in excellent service design (Frei, 2008). In the sharing economy, the platform is not a direct provider of services, but a medium that uses information technology to establish a connection between service providers and service recipients (Katz, 2015). The platform, service providers and service recipients make up a service system and network (Normann and Ramirez, 1993). Optimizing the service network to improve customer satisfaction turns into an important topic in service research (Ostrom et al., 2010). Therefore, it is critically important for academics and practitioners to understand how online car-hailing businesses can establish the service quality management capability to optimize and innovate their service

[1] http://tech.sina.com.cn/roll/2018-01-08/doc-ifyqiwuw8089887.shtml
[2] https://www.recode.net/2018/1/5/16854714

design.

Prior literature on online car-hailing mainly focuses on comparing it to traditional taxis (Donald and Anderson, 2014; Rayle et al., 2016); exploring its regulations (Witt, Suzor and Wikström, 2016; Zha, Yin and Yang, 2016) and governance (Li, Taeihagh and Jong, 2018); and understanding consumer behaviors from a user perspective (e.g., the unified route choice model (Xu et al., 2017) and the behavioral choice model (Dias et al., 2017)).

However, this body of research has overlooked insights from the service literature and is unable to provide insights on the aforementioned quality issues. Additionally, empirical findings are scant in the studies of service quality in the sharing economy context (Priporas et al., 2017), particularly the service quality of online car-hailing.

Aiming at these shortcomings, this paper takes a service quality perspective to address the service issues of online car-hailing. We develop a model of service optimization and propose a research framework for the service quality management of online car-hailing in the sharing economy. We use data mining techniques and methods, including text classification, sentiment analysis and frequent itemset mining, to identify service issues from electronic word-of-mouth (eWOM). We also use process chain network (PCN), an effective visualized tool for service networks, to depict the service process of online car-hailing and achieve service optimization.

The main contributions of this study are twofold. First, it adds to the literature by building a research framework for the service quality management of online car-hailing in the sharing economy, and this framework combines insights for both sharing economies and service literature. This approach addresses the weakness of prior studies that put the emphasis merely on concepts (Felson and Spaeth, 1978; Fitzsimmons, 1985; Lanier and Schau, 2007; Belk, 2010; Bardhi and Eckhardt, 2010) and business models (Zervas, Proserpio and Byers, 2013; Rogers, 2015), but not service quality *per se*. This study focuses on streamlining the service design of online car-hailing by using PCN to depict the service process and optimizing service based on the PCN's optimization principles; therefore, the study provides useful findings on how businesses can improve their service quality.

Second, this study applies PCN and data mining methods to verify the research framework, enabling both academic and practical implications. The study adds to the PCN literature

(Sampson, 2012) by applying it to the scope of the service process depiction and service optimization of online car-hailing, forming a novel effort. In addition, this study uses data mining to identify the service issues from eWOM of online car-hailing platforms. Specifically, it constructs an LSTM text classification model to examine passenger comments from eWOM, extracts negative comments via sentiment analysis and then addresses the service issues with frequent itemset mining. These research findings help to provide useful ideas for online car-hailing platforms to explore their service quality problems, optimize and innovate their service design, and improve their service quality management capability. This study also provides valuable implications for online car-hailing platforms to mine more useful knowledge from big data generated by users and satisfy them with better services.

## 2. Background and literature review

### 2.1. Sharing economy and online car-hailing sector

With the emergence of sharing economy platforms represented by DiDi, Uber, Airbnb, etc., researchers have tried to describe and define the sharing economy on the theoretical level (Porter and Kramer, 2011; Belk 2014; Matzler et al., 2015). The first concept related to the sharing economy was called collaborative consumption, which represented one or more persons consuming economic goods or services with others when engaging in joint activities (Felson and Spaeth, 1978). In addition, consumer participation (Fitzsimmons, 1985), co-creation (Lanier and Schau, 2007), sharing (Belk, 2010), access-based consumption (Bardhi and Eckhardt, 2010), etc., were also used to describe sharing economy behavior and phenomena.

Since its emergence, the sharing economy has been developing rapidly and impacting various industries and society as a whole. A body of studies describe this new form of economy and its impact (Zervas, Proserpio and Byers, 2013; Schor, 2014; Rogers, 2015). According to Schor (2014), the sharing economy platform establishes a connection between service providers and service recipients through Internet technology, thereby reducing the transaction cost of sharing, establishing trust mechanisms in multiple ways, and making the sharing economy model sustainable. Indeed, its prospect is largely recognized by industry and academia (Möhlmann, 2015), and has been envisaged as an important economic model (Heo, 2016).

However, behind the rapid development and increasing popularity, some issues appear. These can be exemplified by Airbnb's negative impact on the ecosystem of traditional hotels and the unemployment rate (Zervas, Proserpio and Byers, 2013), as well as the social costs (i.e., security, personal privacy and discrimination) of Uber's business model (Rogers, 2015). As a result, activists and politicians have called for a more complex legal structure and regulations to deeply regulate or even exterminate sharing economy businesses.

Researchers have undertaken studies of the potential issues from different perspectives. For example, Cheng's (2016) review of the sharing economy revealed three key themes, including the business model and its impacts, the nature, and the sustainable development, among which the business model and its impacts is the most dominant broad area. The business models of the sharing economy range from online car-hailing to short-term rental, financial sharing to knowledge sharing. Online car-hailing is one of the most typical modes.

Online car-hailing, also called real-time ride sharing, ride-hailing, on-demand rides and ride-sourcing (Rayle et al., 2016), is a typical service form in the sharing economy. It is a service that allows drivers and passengers to arrange one-time shared rides ahead of time or on short notice (Amey et al., 2011). Since its emergence, there existed many issues (e.g., service quality, regulations, and conflicts with the traditional taxi industry). Nevertheless, as a service form of sharing economy, it gathers drivers, passengers, governments, and payment companies through the Internet. It solves the problems of idle resource utilization and information asymmetry through an efficient matching mechanism and realizes the transformation of traffic resources from ownership to access rights. Therefore, how to solve the existing issues and exert advantages to promote the healthy growth of the sharing economy becomes an important task.

### 2.2. Service quality in the sharing economy

The service literature highlights the importance of service quality as a source of firm competitiveness. Grönroos (1989) applied the psychology theory in his seminal work to define service quality as the gap between the customer's expected service and perceived service. Following this perceived service quality model, researchers have explored the dimensions and measurement indicators of service quality, and this exploration led to more service quality models (Brady et al., 2005; Liljander and Strandvik, 1995). Among them, the work of Parasuraman, Zeithaml and Berry attracted great attention. Parasuraman et al. (1985, 1988) proposed a service quality gap model and identified ten aspects affecting service quality. A development by Parasuraman et al. (1991) is the SERVQUAL model explaining five dimensions including reliability, responsiveness, assurance, empathy and tangibility.

To capture the concept in the current information age, researchers have developed the online service quality (e-SQ) (Zeithaml, Parasuraman and Malhotra, 2002), electronic service quality (E-S-QUAL) (Parasuraman et al., 2002) and other service quality assessment tools. However, the prior literature has only focused on traditional industries (e.g., banking, credit cards, appliance repairing and maintenance, and long-distance communication (Parasuraman et al., 1988)), while few studies have evaluated service quality in emerging industries, namely, the sharing economy. The only study that considered service quality in the sharing economy was particularly on Airbnb (Priporas et al., 2017). Research exploring the service quality of online car-hailing is still in its infancy.

Furthermore, prior research on the sharing economy is mainly limited to defining and explaining the phenomenon of the sharing economy (Felson and Spaeth, 1978; Fitzsimmons, 1985; Lanier and Schau, 2007; Belk, 2010; Bardhi and Eckhardt, 2010) and its business models (Zervas, Proserpio and Byers, 2013; Rogers, 2015), without drawing insights from service quality. In the case of online car-hailing, although prior studies saw initial efforts to apply economic theory to address the development of online car-hailing (Zha, Yin and Yang, 2016), researchers welcome opportunities to integrate more theories and multiple-level analyses to allow for multidisciplinary and context-rich investigations (Cheng, 2016). Service-dominant logic (Vargo and Lusch, 2004) suggests that service is at the center of all economic activities. Therefore, the sharing economy is actually a type of service economy and it is necessary to apply service science theory to sharing economy research.

### 2.3. Process Chain Network

Improving service quality highly depends on excellent service design (Frei, 2008). Shostack (1984) proposed the concept of service blueprinting. By using a qualitative analysis of the service process with an intuitive flow chart, blueprinting can specify important elements in the service system, including the service process, service encountering points, provider actions, customer actions, physical evidence, and service support processes (Shostack, 1992). As an important tool to improve service quality and achieve service innovation, service blueprinting has been widely applied in various industries (Bitner et al., 2008) .

Normann and Ramirez (1993) pointed out that a service system is essentially formed by the interactive activities of multiple parties and mutual interactions. Optimizing the service network to improve customer satisfaction is an important topic in service science (Ostrom et al., 2010). In the sharing economy, platforms link service providers and recipients together efficiently with modern information technology (Schor, 2014). These three participants form a service network (Normann and Ramirez, 1993). However, due to the complex interaction among various entities in a multiparticipant service network, service blueprinting has obvious limitations when applied to analyze the sharing economy service network. Sampson (2012) proposed a PCN methodology to clearly depict the complex interactions among multiple entities in a service network. The PCN sequentially depicts each step in the service process according to the type of interaction among entities, thereby overcoming the limitations of service blueprinting. In addition, the PCN's optimization principles also help to optimize the service process.

Instead of simply explaining the actions between service providers and consumers, the PCN captures the interactions between participating entities involved in the service process through three types of regions relating to direct interactions, surrogate interactions and independent processing. A direct interaction means that an entity interacts with another one directly; a surrogate interaction means that an entity interacts with another one by involving the nonhuman resource of another entity; and independent processing means that an entity processes independently without involving either direct or surrogate interaction with other entities (Sampson, 2012). Kazemzadeh, Milton and Johnson (2015a) compared the concepts in service blueprinting and PCN, finding that PCN provides a better insight about the nature of interaction between participating entities involved in the service process and is therefore more appropriate for application to managerial issues, such as process efficiency and customization. Their ontological comparison of service blueprinting and PCN also concluded that PCN is a more promising way to depict the complex interaction of service processes where entities provide services in collaboration (Kazemzadeh, Milton and Johnson, 2015b). Therefore, we use PCN rather than service blueprinting to analyze the complex interactions between the three participants in the online car-hailing service network.

### 2.4. Research framework

eWOM has been proven to have a significant impact on consumers' purchase decisions (Park and Lee, 2009; Wang, Wang and Wang, 2018). Moreover, negative comments were found to have a more significant impact on consumers (Pan et al., 2018). Firms need to quickly find their own service issues through mining eWOM. Chang and Wang (2018) conducted a sentiment analysis on online comments regarding Airbnb and HomeAway and found that emotions expressed in comments influence consumers' decisions. Therefore, we first collected the eWOM data of online car-hailing and extracted the passenger comments with an LSTM text classification model to address the service issues. We then used PCN to depict the online car-hailing service network, analyze and locate the service issues, and finally explore the optimization strategy for improving online car-hailing service quality. The research framework is shown in Fig. 1.

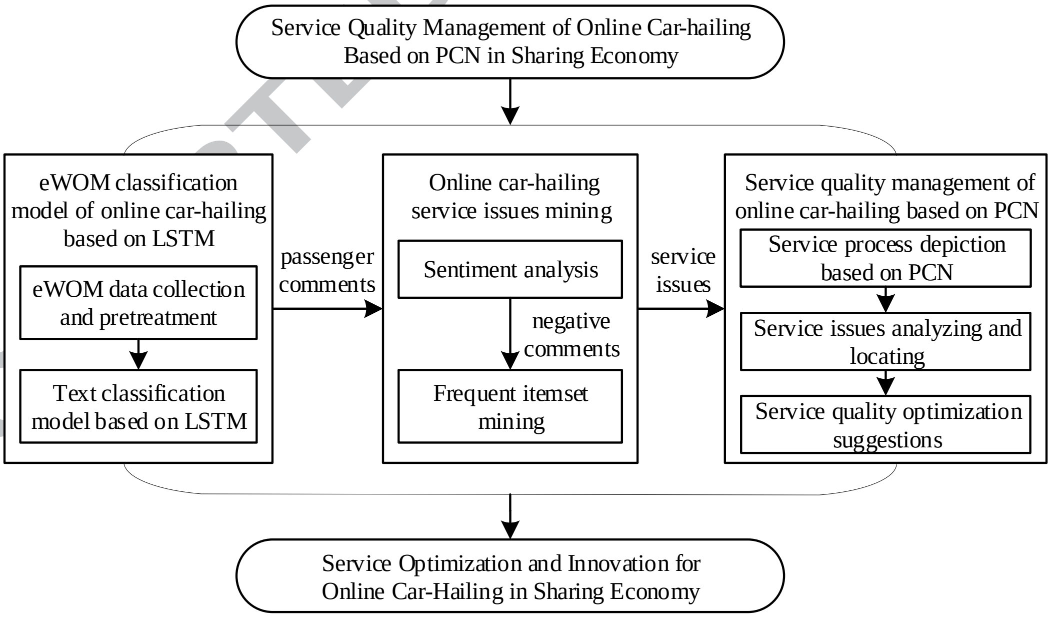


Fig. 1. Research framework

## 3. eWOM classification model of online car-hailing based on LSTM

### 3.1. eWOM data collection and pretreatment

This study used Sina Weibo as the source of eWOM data and collected microblog texts related to the DiDi platform. Sina Weibo is China's most popular microblog platform with 340 million monthly active users, surpassing Twitter to become the largest independent social media company in the world[3]. The communication and sharing of the massive number of users on Sina Weibo have generated much content and information through the site's microblogs.

We checked the microblog posts on Sina Weibo and found that the user sentiment expressed in microblogs containing the string "@XXX" were stronger. Moreover, due to the characteristics of Sina Weibo, microblogs containing keywords such as "@Didichuxing" were more relevant to Didi Chuxing, compared to keywords without any symbols. These microblogs would be more meaningful for mining the service issues of online car-hailing. Therefore, we used Sina Weibo's search engine with keywords (in Chinese), such as @Didichuxing, @Dididache and @Didikuaiche, and collected the search results, which included three sets of content related to the microblog publisher, the microblog text and the microblog posting time. Microblogs with a text length of fewer than ten words, and strings without semantic information, such as "#XXX#", "@XXX", place, URL, punctuation, etc., were filtered. For example, strings such as "#Dididache#" and "#Honey 520#", which were usually the headlines of "marketing" microblogs, were filtered. Search keywords such as "@Didichuxing" and "@Didikuaiche" were also filtered. After preprocessing the eWOM data, we obtained a dataset of 4,331 microblogs. The posting time spanned from January 2016 to June 2017.

The dataset contains three types of microblogs, posted by online car-hailing passengers, drivers and DiDi. We constructed a text classification model to classify the microblogs into these three classes. We manually labeled the microblogs into three classes including "passenger", "driver" and "marketing" for the subsequent training of text classification. Each microblog was labeled according to its syntactic structure, expression manner or tone. For example, microblogs such as "the ride was an unpleasant experience this evening…" would be labeled "passenger", those such as "just because of being too close to the passenger, I was assigned twice and fined twice by DiDi in half a month...." would be labeled "driver", and microblogs starting with a headline such as "#XXX#" related to the platform's marketing

[3] http://intl.ce.cn/specials/zxgjzh/201705/16/t20170516_22895502.shtml

activities would be labeled "marketing". The labeled examples are shown in Table 1. After that, we obtained a total of 4,331 microblogs, including 3,292 "passenger" microblogs, 401 "driver" microblogs and 638 "marketing" microblogs.

Table 1. Microblog examples

| Microblog text | Label |
| --- | --- |
| The ride was an unpleasant experience this evening. It was the first time I had encountered such a deliberate detour since I used DiDi… | passenger |
| …I think that @Didichuxing you need to provide the driver's contact information at least, or you can solve this problem through customer service. How can such a driver be reassuring… | passenger |
| Just because of being too close to the passenger, I was assigned twice and fined twice by DiDi in half a month. @Didikuaiche… | driver |
| …If DiDi wants to develop in the long run, it must pay more attention to drivers' interests. You should reduce the rate of commission and tear up the overlord clauses… | driver |
| #Go for a journey#...DiDi is a product that conforms to the trend of the times. It is fast, it is convenient, it is a symbol of the times… | marketing |
| #Five safety technologies of DiDi# We guard your safe trip together, in case of emergency, remember to use the help function by pressing the button… | marketing |

**3.2. Word embedding**

Text representation and feature extraction are fundamental problems of text mining. The bag of words is the most common method for text feature extraction. However, feature representation methods based on the bag of words ignores important information, such as the context of the text and semantics of the words. For example, under the hypothesis of the bag of words, both of the following sentences (in Chinese) “Drivers should respect the passenger” and “Passengers should respect the driver” can be represented by the same vector $(1, 1, 1, 1, 1)^T$, and can't be distinguished by the classification model. In 2013, Google released an efficient training tool for word embedding, word2vec. For a given corpus, after training with word2vec, each word can be mapped into a word vector with specific dimensions. Word2vec can be trained efficiently on large corpora to get word embeddings that retain the semantic information to a large extent and can be used as the input of neural network, such as LSTM.

Therefore, we used word2vec for word embedding to solve the feature extraction problem of the bag of words. We took the Chinese Wikipedia Corpus as the training corpus for word embedding to avoid overfitting in processing the Sina Weibo dataset and making the following LSTM model more robust. The dimension of the word vector was set to 200. After the training, we obtained the word vectors to be used in the LSTM text classification model.

### 3.3. Text classification model based on LSTM

Recurrent Neural Networks (RNN) (Mikolov et al., 2013b) and Long Short Term Memory networks (LSTM) (Rumelhart et al., 2014) are the two most commonly used neural network models for text classification. RNN compresses historical information by introducing the concept of time. The contextual information can be memorized in the neural network so that the semantics of the text can be more fully learned. However, RNN has the problems of both short-term memory and vanishing gradient. On the basis of RNN, LSTM introduces a well-designed structure, *cell*, to effectively alleviate these two problems, making it the most popular neural network in practical applications (Goodfellow et al., 2016). In this study, we constructed an LSTM text classification model to automatically classify the microblogs. The specific structure of the LSTM neural network is shown in Fig. 2.

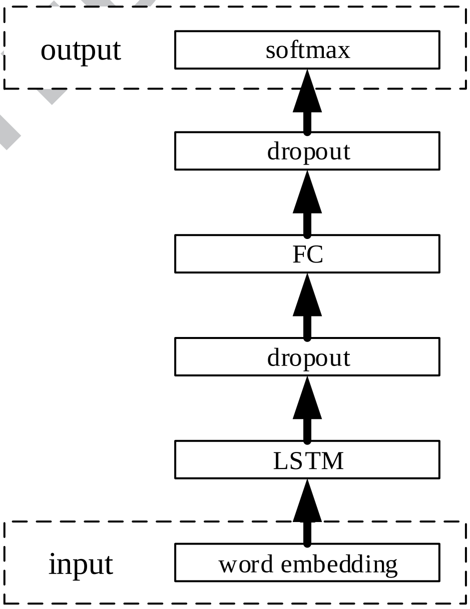


Fig. 2. Text classification model based on LSTM

As shown in Fig. 2, FC is a fully connected layer, while dropout (Srivastava et al., 2014) is a layer that removes some hidden nodes randomly during training, and this removal can effectively prevent overfitting and improve the generalization of the model. The dropout layer can also obtain the effect of ensemble learning with lower cost and enhance the robustness of the model. Softmax outputs the probability of the microblog belonging to different classes by normalizing multiple outputs and is calculated as shown in formula (1). Each microblog was predicted to belong to one of the three classes, "passenger", "driver" or "marketing", according to the maximum probability of the softmax function output.

$$\text{softmax}(x)_i = \frac{\exp(x_i)}{\sum_{j=1}^{n}\exp(x_j)} \tag{1}$$

We used the Chinese Word Segmentation tool, Jieba, to conduct word segmentation on microblog texts. For each word in word segmentation, the corresponding word vector is obtained from the word abovementioned embedding pretrained using word2vec (Mikolov et al., 2013a). The word vectors are used as input for the LSTM neural network. We further took TensorFlow as the calculation engine and used the deep learning open source framework, keras, to implement the text classification model shown in Fig. 2. The main parameters in the experiment are shown in Table 2.

Table 2. Training parameter settings

| Layer | Parameter | Value |
|---|---|---|
| word embedding | input_length | 28 |
| LSTM | units | 64 |
| | dropout | 0.2 |
| | recurrent_dropout | 0.2 |
| dropout | rate | 0.5 |
| FC | units | 32 |
| | activation | relu |
| dropout | rate | 0.5 |
| softmax | units | 3 |
| | activation | softmax |

We sampled 80% of the labeled microblogs as the training set and 20% of that as the test set. In training, batch_size was set to 30, nb_epoch was 20, and the optimization algorithm was set as Adam (Kingma and Ba, 2014). After training, the model correctly predicted 789 of the 868 test samples, with an accuracy of 90.89%, which shows the reliability of the LSTM model on microblog classification, or "passenger" microblogs extraction.

## 4. Online car-hailing service issues mining

### 4.1. Sentiment analysis

Sentiment analysis is an important research topic in the field of natural language processing that can be used to mine and analyze users' emotions and opinions contained in text (Wilson, Wiebe and Hoffmann, 2005). Our initial data included both negative comments and positive comments about online car-hailing services. However, the goal of this study is to mine the service issues of online car-hailing by analyzing the passengers' negative comments. Therefore, it is necessary to use sentiment analysis to analyze the sentiment orientation of passenger comments and extract the negative comments. To achieve this goal, we performed sentiment analysis on the passengers' comments using SnowNLP, a Chinese natural language processing tool. For each input comment, SnowNLP predicts the sentiment orientation of the text through the trained model and outputs a probability value between 0 and 1, which indicates the probability of this text being positive. In this study, the threshold is set to 0.5, and the comments with output probability values less than 0.5 are classified as negative comments and extracted. Finally, 2,946 negative comments were identified among the 3,292 passenger comments.

### 4.2. Frequent itemset mining

The word segmentation result is regarded as one transaction, and each word is considered one item, so the task of service issue mining can be transformed into the task of frequent itemset mining. We can use frequent itemset mining to extract frequent co-occurrence words from the passengers' negative comments and further find the service issues of online car-hailing by analyzing the mining results.

Apriori (Agrawal and Srikant, 1994) and FP-Growth (Han and Fu, 1995) are the two basic algorithms used for frequent itemset mining. The Apriori algorithm generates a large number of candidate frequent itemsets in the process of generating frequent itemsets through multiple iterations. In each iteration, the algorithm needs to scan the whole dataset repeatedly and count the candidate frequent itemsets to filter the infrequent itemsets, making the algorithm inefficient. The FP-Growth algorithm compresses the transaction database to be mined into a frequent pattern tree (FP tree) to avoid generating a large number of candidate frequent itemsets, and only needs to scan the dataset twice to complete the task of frequent itemset mining.

This study implemented the FP-Growth algorithm to mine the frequent itemsets from passengers' negative comments. First, we carried out word segmentation and stop-word filtering on passengers' negative comments. Then, we conducted frequent itemset mining based on the FP-Growth algorithm to mine the service issues of online car-hailing. Of the frequent itemsets output by the FP-Growth algorithm, the following three types were filtered:

(a) Frequent itemsets with a single item. A high-frequency word is invalid to reflect the service issues and it is useless for this analysis.

(b) Any group of words that frequently appear in the field of online car-hailing. For example, a group of the words "Driver", "Passenger", "Customer Service", or "DiDi" usually has a high support degree but is invalid to reflect the service issues. Therefore, frequent itemsets such as <Driver/Passenger> and <Driver/DiDi> were filtered.

(c) Any subset of maximal frequent itemsets. Since any subset of a frequent itemset is also a frequent itemset, we only need to preserve maximal frequent itemsets to keep the results simple and not lose the useful information at the same time. For example, we only retained the maximal frequent itemset < Driver/Cancel/Order >, and its subsets < Driver/Cancel >, < Driver/Order > and < Cancellation/Order > were filtered.

Finally, we obtained the frequent itemsets that are useful in analyzing the service issues of online car-hailing. The top 22 frequent itemsets (translated into English) and their support degrees are shown in Table 3.

Table 3 Frequent itemset mining results

| Frequent Itemsets | Support Degree | Frequent Itemsets | Support Degree |
|---|---|---|---|
| Complaining/Driver | 0.1049 | Telephone/Cancellation | 0.0346 |
| Driver/Call | 0.0754 | Driver/Trip | 0.0339 |
| Driver/Cancel/Order | 0.0686 | Call/Customer Service | 0.0322 |
| Waiting/Driver | 0.0462 | Driver/On-Vehicle | 0.0316 |
| Driver/Mobile Phone | 0.0438 | Cancellation/Call | 0.0312 |
| Customer Service/Complaint | 0.0418 | Contact/Customer Service | 0.0302 |
| Driver/Contact | 0.0387 | Complaint/Cancellation | 0.0292 |
| Driver/Attitude | 0.0380 | Not/Familiar with/Route | 0.0289 |
| Telephone/Complaint | 0.0370 | Driver/Detour | 0.0282 |

| | | | |
|---|---|---|---|
| Driver/Quality | 0.0360 | Not/Find | 0.0282 |
| Driver/Call/Telephone | 0.0353 | Driver/Service | 0.0282 |

## 5. Service quality management of online car-hailing based on PCN

### 5.1. Service process depiction based on PCN

According to Yang and Xu (2016), the service process of online car-hailing contained three sub processes: placing an order, traveling and paying. Zuo and Chen (2017) used service blueprinting to depict the service process of the sharing economy, including selecting a channel, accessing a platform, matching demand, paying, waiting for service, receiving service and evaluation. Through continuous discussions, we divided the service process of online car-hailing into four sub processes: a passenger initiates a request to the platform; the platform sends the order to a driver; the driver picks up the passenger; and the passenger pays and evaluates. Taking the DiDi platform as an example, the detailed sub processes are as follows:

(a) A passenger initiates a request to the platform. The passenger generates a car-hailing request. S/he inputs the information of the pick-up location, the destination and the vehicle type for the trip by using the client application of the DiDi platform, and then initiates a request to the platform and waits for the driver to pick them up at the pick-up location.

(b) The platform sends the order to a driver. After the platform receives a car-hailing request from a passenger, the system first analyzes the request and sends the analysis result to the order dispatching system. The order dispatching system assigns a driver according to a certain matching algorithm, and then dispatches this order to the specific driver.

(c) The driver picks up the passenger. After receiving the order, the driver first calls the passenger to confirm the pick-up location. Reaching an agreement on the pick-up location with the passenger, the driver will approach the pick-up location to pick up the passenger. When the driver arrives at the pick-up location, the passenger gets on, and the driver starts billing on the driver client application and then takes the passenger to the destination. After arriving at the destination, the driver ends billing, and the passenger gets off.



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(d) The passenger pays and evaluates. If the passenger has no objection to the service, s/he pays the fare on the client application and evaluates the driver's service quality. The car-hailing service ends here. However, if the passenger has any objection to the service, s/he would call the customer service of the platform to make a complaint. Then, the customer service would deal with the problem that the passenger has reported.

According to the analysis results of the online car-hailing service process, we further used a PCN to depict the service process and explain the interaction between driver, passenger and platform in more detail. In accordance with the steps of establishing a PCN diagram (Sampson, 2012), we depicted the PCN of online car-hailing as follows:

(a) Understanding the service process to be analyzed. In this study, we analyzed the online car-hailing service network by taking the DiDi platform as an example. Therefore, the object of the analysis is the service process of the DiDi platform.

(b) Identifying multiple entities involved in this process. There are three entities involved in the service process, including the driver, the passenger and the platform.

(c) Analyzing the starting and terminating steps of the process and depicting them in the PCN diagram. In the service process of the DiDi platform, the starting point of the service is that a passenger initiates a request to the platform. After the driver successfully delivers the passenger to the destination, the passenger pays the fare, and the service process ends.

(d) According to the order of each step in the service process and the process region to which the step belongs, all intermediate steps are listed in the PCN diagram, and the order and dependency relationship between two steps is represented by an arrow.

Based on the analysis results obtained above, a PCN diagram of the service network of the DiDi platform is established. The results are depicted in Fig. 3.

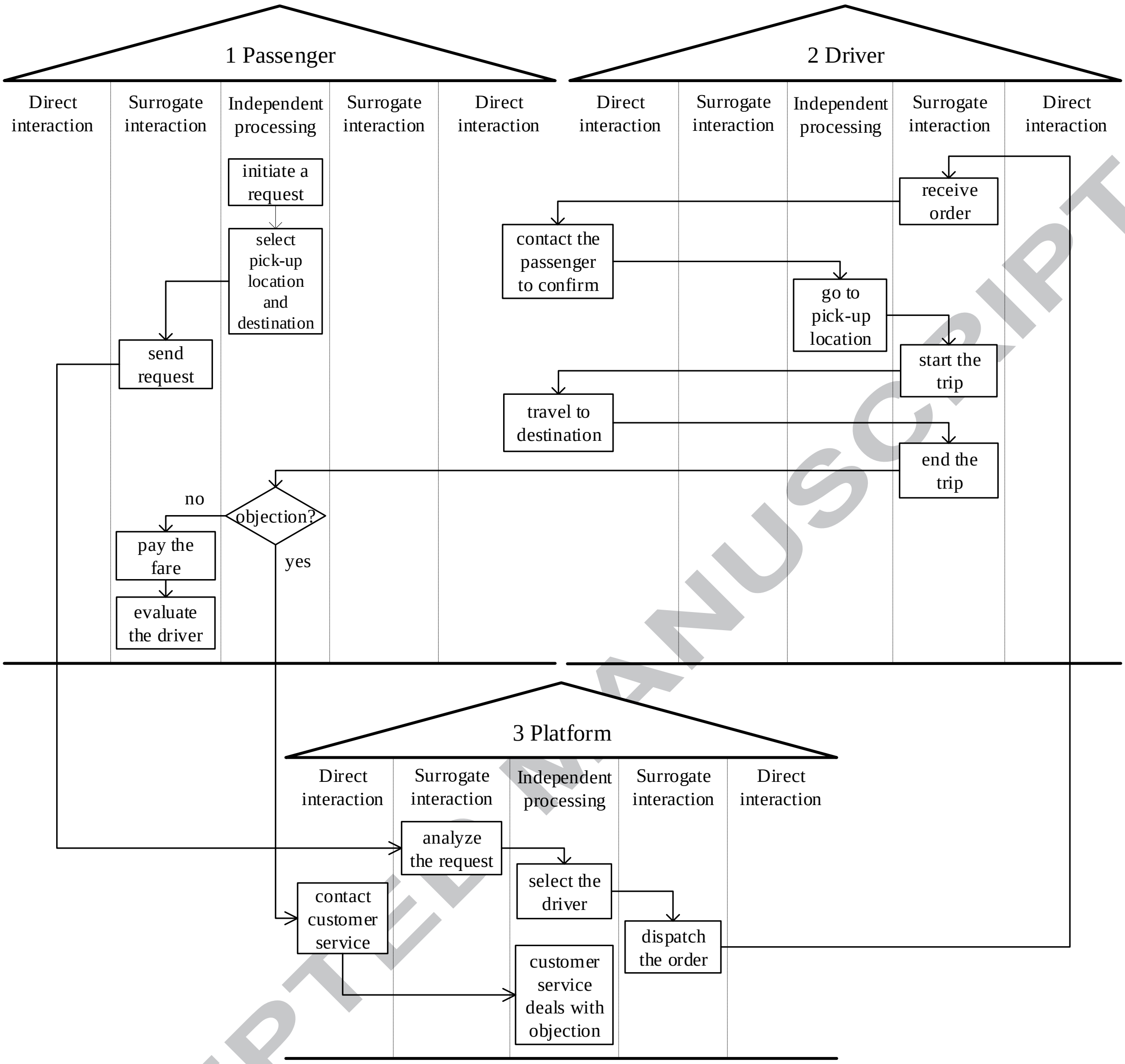


Fig. 3. PCN diagram of online car-hailing service

## 5.2. Service optimization and innovation

Based on the mining results of online car-hailing service issues above, we then analyzed and located the service issues in the PCN in order to propose the corresponding service quality optimization suggestions based on the optimization principles of the PCN, including process inefficiency, economies of scale, customization and surrogate positioning. The efficiency of direct interaction is lower than that of independent processing, while the customization of direct interaction is higher than that of independent processing. The efficiency or customization of surrogate interaction is between that of direct interaction and independent processing (Sampson, 2012). Thus, the application of these principles is actually a trade-off between efficiency and customization.

To identify the service issues existing in the service process of the PCN, we map the frequent itemsets mentioned above to the sub processes of the PCN. Two main criteria are considered in the mapping process: (1) a frequent itemset was mapped to the corresponding entity region (passenger, driver and platform) according to the entity and actions it contained or reflected; and then (2) the frequent itemset was mapped to the corresponding sub process (direct interactions, surrogate interactions and independent processing) according to the service issues it reflected. To identify the corresponding service issues reflected by a frequent itemset, we checked the users' detailed description in the original microblog by examining the co-occurring item words of the frequent itemset in the microblog dataset, ensuring that we got the right criticalities lying behind the microblog containing those words.

#### 5.2.1. Establishing "virtual sites"

According to the principle of process inefficiency, direct interaction is the least efficient of the three types of process region, as customers engaging in self-service surrogate interaction or do-it-yourself independent processing are usually not paid by the provider firm for their efforts so that they represent efficiency to the firm (Sampson, 2012). In the PCN diagram of DiDi (Fig. 3), the driver's contacting the passenger to confirm the pick-up location is in the region of direct interaction. The frequent itemsets, such as <Driver/Telephone, 0.0754>, <Driver/Call/Telephone, 0.0353>, <Driver/Contact, 0.387>, and <Driver/Telephone, 0.0438>, are just the reflection of this interaction. However, interactive service where the driver contacts the passenger to confirm the pick-up location does not directly contribute to the value of the service system and could be regarded as a useless interaction in the service process. According to the principle of process inefficiency, the efficiency of the service system can be improved and the service process can be optimized by converting direct interaction into surrogate interaction or eliminating useless interaction (Sampson, 2012). In addition, the frequent itemset <Not/Find, 0.0282> explains the fact that the driver may not be familiar with the environment of the pick-up location or that the positioning of the passenger's mobile phone is inaccurate, so that it becomes a common case that the specific pick-up location of the passenger cannot be found.

Based on the two service issues mentioned above, we suggest that the platform can perform clustering analysis of passengers' pick-up location data accumulated in the data warehouse and build a "virtual site" for passengers to board on the basis of the analysis results and the map database. Under such a mechanism, the driver only needs to reach the virtual site to pick up the passenger after receiving the order, instead of calling the passenger to confirm the pick-up location. This can effectively eliminate the useless interaction between the driver and the passenger confirming the pick-up location and improve the efficiency and the quality of the online car-hailing service, as this interaction can prevent the driver from finding the passenger when he is unfamiliar with the route or when the positioning of the passenger's mobile phone is inaccurate. In addition, the platform does not need to establish a physical site in the real environment and only needs to provide the site's location information and pictures so that the passengers and drivers can identify the location of the site. Therefore, this scheme is feasible in terms of implementation cost. With the introduction of the "virtual site", passengers no longer casually choose the pick-up location. Therefore, the step of contacting the passenger to confirm is removed, while the step of selecting pick-up location and destination turns into selecting a virtual site and destination and moves from the region of the passenger’s independent process to that of the passenger’s surrogate interaction in the PCN diagram. The establishment of the "virtual site" in the process of the PCN is depicted in Fig. 4 (a).

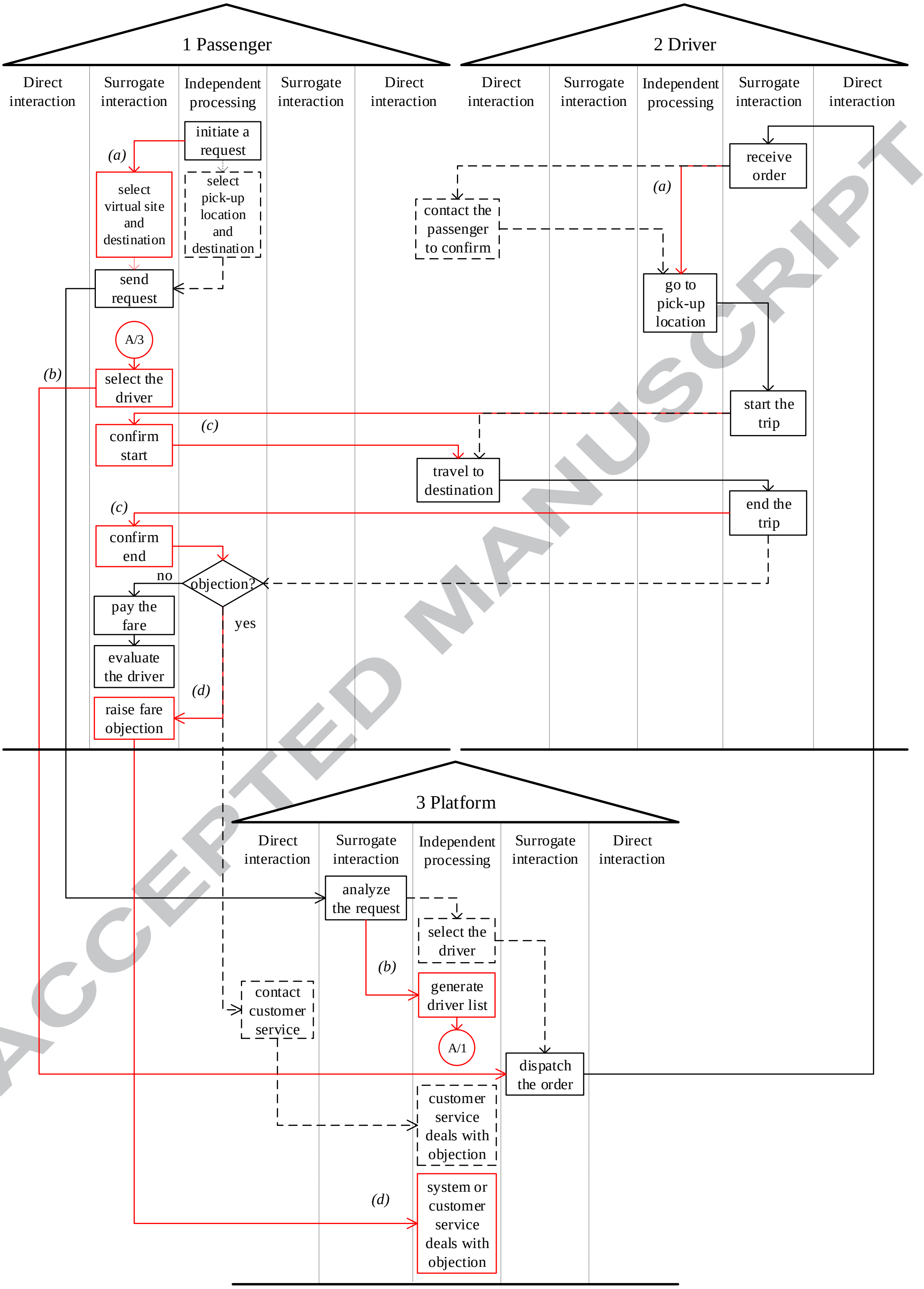


Fig. 4. Service optimization of online car-hailing based on the PCN

### 5.2.2. The introduction of the "selecting driver" function

The frequent itemsets, such as <Driver/Attitude, 0.0380>, <Driver/Quality, 0.0360>, and <Not/Familiar with/Route, 0.0289>, reveal the service issues of drivers having poor professional quality, poor service attitudes or a lack of professional skills, and the frequent itemset, <Waiting/Driver, 0.0462>, reflects that the passenger waits too long for the driver to pick them up after initiating a request to the platform.

Although the platform can force the drivers to improve service quality and professional skills to some extent by introducing a scoring mechanism, the service failure will be attributed to the fact that the platform's dispatching results are not satisfactory when the passenger waits for the driver for a long time, because the passenger does not have the opportunity to select a driver and the driver is just assigned by the platform. According to the principle of customization, when the process steps are located in the region of the provider's independent process, the level of customization is the lowest, and as the process steps move to the consumer's independent process, the level of customization increases (Sampson, 2012). In the PCN diagram of DiDi (Fig. 3), selecting a driver is located in the region of the independent process, so the customization level of this mechanism is not high enough. The level of customization can be increased by adding the step of generating a driver list in the region of the platform’s independent process and moving the step of selecting a driver from this region to that of the passenger’s surrogate interaction.

Therefore, we propose that, after the platform receives and processes the passenger’s request, it can provide the passenger with a list of available drivers so that the passenger can choose a driver by himself/herself. Thus, the step of selecting a driver is moved from the region of the platform’s independent process to that of the passenger’s independent process. Then, the platform dispatches the order to the appropriate driver based on the passenger's choice. When allowed to select drivers by themselves, passengers would think that they have to bear some responsibility for the service failure when they are not satisfied with the service and try to find the reason, because it is passengers themselves who decide their own drivers (Hubbert, 1995), and this can decrease the level of dissatisfaction with the platform. Moreover, different passengers have different needs for online car-hailing services. For example, some passengers are in a hurry so they are more concerned with how long it will take the drivers to reach the pick-up location and hope that the driver is close to them. Some passengers have just finished their tiring work and want to rest quietly in the car for some time, so they hope that the driver will be stable and quiet. Some passengers may have just arrived in a city for the first time and want to find a local driver as a guide. Provided with the opportunity to decide drivers on their own, passengers can satisfy their needs and get better service. The introduction of the "selecting driver" function in the process of the PCN is depicted in Fig. 4 (b).

#### 5.2.3. The introduction of the "confirming getting on and off" function

The frequent itemset, <Driver/Trip, 0.0339>, reflects the passenger's perception that the trip billing of the service is inconsistent with the actual trip, including the fact that the driver has already started billing before the passenger boards, or that the passenger has already got off but the driver has not yet ended billing. As shown in the PCN diagram of DiDi (Fig. 3), this is caused by the fact that both the beginning and the ending of the trip are located in the region of the driver’s surrogate interaction, without passengers’ participation. Therefore, passengers need to be introduced into the operation of confirming the starting and ending of billing to avoid this issue from the service operation mechanism. The frequent itemset, <Driver/On-Vehicle, 0.0316>, reflects the issue that passengers often leave personal belongings in the car. Moreover, this study also finds that the support degree of the itemset, <Mobile Phone/Driver/On-Vehicle>, reached 0.0129. Combined with the frequent itemset, <Driver/On-Vehicle, 0.0316>, it is indicated that mobile phones are the belonging that passengers usually leave in the car.

From the principle of customization (Sampson, 2012), we propose that the platform can introduce interactive operations for passengers to confirm getting on and off, thereby improving the customization level. On the one hand, this can avoid the problem of trip billing being inconsistent with the actual trip from the service operation mechanism. On the other hand, the operation of confirming getting off ensures that the passenger has taken his/her mobile phone when getting off. As such, the step of confirming start and finish are added to the region of passengers’ surrogate interaction. The introduction of the "confirming getting on and off" function in the process of the PCN is shown in Fig. 4 (c).

#### 5.2.4. The introduction of the "fare objection" function

The frequent itemset, <Driver/Detour, 0.0282>, reflects the issue of drivers' detouring. To solve this service issue, the DiDi platform has already introduced the "fare objection" function. The platform's background system can automatically determine whether the driver has made a detour by comparing the driving route generated by the path planning algorithm with the actual driving track of the vehicle. If the background system finds detouring behavior, it will actively provide feedback to the passenger. If the passenger suspects that the driver has made a detour, s/he can also make a complaint about the driver's detouring by using the "fare objection" function when paying for the order, and the background system will further deal with the problem.

However, the traditional approach is that passengers call the platform's customer service to make a complaint and then wait for the processing result. As in the PCN diagram of DiDi (Fig. 3), the process of passengers' calling and complaining to the customer service is located in the region of direct interaction. According to the principle of process inefficiency, the efficiency of the direct interaction process is the lowest (Sampson, 2012). By using the "fare objection" function, passengers can directly provide feedback about their problems using their mobile client application when they have objections to the trip. This step is located in the region of the passenger's surrogate interaction. Then, the background system or the customer service of the platform will deal with the problems, which are located in the region of the platform's independent processing. Therefore, the step of contacting custom service turns into raising a fare objection and moves from the region of direct interaction to that of the passenger's surrogate interaction, and the step of customer service's dealing with objection in the region of the platform's independent processing turns into the system or customer service's dealing with the objection, thus improving the efficiency of the service system. The introduction of the "fare objection" function in the process of the PCN is depicted in Fig. 4 (d).

#### 5.2.5. Other issues

The frequent itemsets, such as <Driver/Cancel/Order, 0.0686>, <Complaint/Cancellation,

0.0292>, <Telephone/Cancellation, 0.346>, and <Cancellation/Call, 0.0312>, reveal the issue of the passenger finding that the driver has canceled the order after s/he initiated a request to the DiDi platform and waited for the driver. This action delays the passenger's trip and affects his/her experience. During the study period, DiDi has set up relevant rules to strengthen the punishment for drivers' arbitrary cancelling of orders, solving the problem to some extent.

The frequent itemsets, such as <Complaint/Driver, 0.1049>, <Customer Service/Complaint, 0.0418>, <Telephone/Complaint, 0.0370>, <Call/Customer Service, 0.0322>, and <Contact/Customer Service, 0.0302>, only reflect passengers' dissatisfaction with online car-hailing service, but do not reflect the specific service issues. Therefore, this study does not conduct an in-depth analysis of these frequent itemsets.

## 6. Conclusions

As a service form of sharing economy, online car-hailing has shown significant growth and service issues, limiting the healthy and sustainable development of the sharing economy. This study takes a service science-based perspective of the PCN to explore the strategy of optimizing the service quality of online car-hailing, and finally constructs the research framework of the service quality management of online car-hailing in the sharing economy. We conclude the research framework as follows.

(1) Collecting the eWOM of online car-hailing and extracting passenger comments from the eWOM by constructing an LSTM text classification model.

(2) Analyzing the sentiment orientation of the text data and extracting the negative comments using the sentiment analysis tool, SnowNLP.

(3) Identifying the service issues of online car-hailing from the passengers' negative comments by implementing frequent itemset mining.

(4) Depicting the service network of online car-hailing, analyzing and locating the service issues of online car-hailing based on the PCN, and then realizing service innovation and optimization according to the service process optimization principles of the PCN.

We propose service quality optimization suggestions based on the service process optimization principles of the PCN, including the establishment of the "virtual site", the introduction of the "selecting driver" function, the introduction of the "confirming getting on and off" function, and the introduction of the "fare objection" function.

This study fills the research gap of the sharing economy from the perspective of service quality, and further enriches the research of online car-hailing and the application scope of the PCN. Moreover, it applies the PCN to depict the service process of online car-hailing, which realizes the innovation of depicting the online car-hailing service process. In addition, the research results also help provide reference for service optimization and innovation of sharing economy platforms and promote the healthy and sustainable development of the sharing economy.

This study also has some limitations that peer researchers may deal with in future research. First, we only use DiDi, the largest sharing economy platform in China, to mine the service issues reflected in its eWOM, excluding others in and out of China. Further research may consider comprehensively evaluating the service quality of online car-hailing from a multiplatform perspective or exploring the differences of service quality among these platforms. In addition, data from surveys, interviews or online public opinions can also be used for research materials. Second, when mining online car-hailing service issues, we only used frequent itemset mining. This traditional mining method may have ignored the semantic information of words, and the mining results contain a small number of frequent itemsets that do not reflect specific service issues. In the age of artificial intelligence (AI), how to use more intelligent methods to mine service issues requires further research.

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1. This work takes a perspective of service quality to study sharing economy.
2. A research framework of service quality management of online car-hailing is proposed.
3. Existing service issues are identified by mining data of electronic word-of-mouth.
4. Strategies of optimizing service quality of online car-hailing are proposed based on PCN.